Algorithm 1 Training Stage of EEG2Video Framework

- **Input:** (1) training set $\mathcal{D}_{train} = \{x_i, v_i, d_i\}$, where x_i is EEG segments, v_i is video clips, d_i is the fast/slow label (2) stable diffusion model T2I, whose VAE encoder is \mathcal{E}_{vae} (3) image caption model B
- **Output:** (1) video diffusion model T2V, (2) Seq2Seq model Seq2Seq, (3) semantic predictor \mathcal{P}_s , (4) dynamic predictor \mathcal{P}_d
- 1: Initialize text prompts of training dataset $T = \{t_i\}$
- 2: for each $(v_i) \in \mathcal{D}_{train}$ do
- 3: $v_i = \{f_1, f_2, \dots, f_n\}$
- $t_i \leftarrow B(f_1)$ 4:
- 5: end for
- 6: Initialize latent vectors of all frames $L = \{z_i\}$
- 7: for each $(v_i) \in \mathcal{D}_{train}$ do
- $v_i = \{f_1, f_2, \dots, f_n\}$ $z_i = \{l_1, l_2, \dots, l_n\}$ for each $(f_j) \in v_i$ do $l_j \leftarrow VAE(f_j)$ 8:
- 9:
- 10:
- 11:
- end for 12:
- 13: end for
- 14: Fine-tune the T2I with $\{v_i, t_i\}$ to obtain video diffusion model T2V
- 15: Train the Seq2Seq model Seq2Seq with all $\{x_i, z_i\}$ using MSE loss
- 16: Train the semantic predictor \mathcal{P}_s with all $\{x_i, t_i\}$ using MSE loss
- 17: Train the dynamic predictor \mathcal{P}_d with all $\{x_i, d_i\}$ using Cross Entropy loss
- 18: return $T2V, Seq2Seq, \mathcal{P}_s, \mathcal{P}_d$

Algorithm 2 Inference Stage of EEG2Video Framework

Input: (1) EEG segments x_i from test set \mathcal{D}_{test} , (2) video diffusion model T2V, (3) Seq2Seq model Seq2Seq, (4) semantic predictor \mathcal{P}_s , (5) dynamic predictor \mathcal{P}_d

Output: reconstructed videos \hat{v}_i ,

- 1: $\hat{z}_i \leftarrow Seq2Seq(x_i), t_i \leftarrow \mathcal{P}_s(x_i), d_i \leftarrow \mathcal{P}_d(x_i)$ 2: Randomly sample $\epsilon_d = \{\epsilon_d^1, \epsilon_d^2, \dots, \epsilon_d^n\}$, each $\epsilon_d^i \sim \mathcal{N}(0, 1)$ 3: Randomly sample $\epsilon_s = \{\epsilon, \epsilon, \dots, \epsilon\}$, where $\epsilon \sim \mathcal{N}(0, 1)$ 4: $z_T \leftarrow \sqrt{\overline{\alpha}_T} \times \hat{z}_i + \sqrt{1 \overline{\alpha}_T} \times (\sqrt{\beta} \times \epsilon_s + \sqrt{1 \beta} \times \epsilon_d)$, where β is determined by d_i
- 5: Generate videos $\hat{v}_i = T2V(z_T, t_i)$
- 6: return \hat{v}_i